Solar Radiation Forecasting Using SVM and Model Averaged ANN Model

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ABSTRACT

Global Solar Radiation (GSR) is a most significant constraint for the performance evaluation of every solar based power station. For realizing the optimum operation of a solar power plant GSR forecasting may play an important role. Hourly day-ahead forecasting can help solar power plant for hourly biding on power exchange to sell their electricity. The present work discusses 1 to 6-day-ahead hourly forecasting using Support-Vector-Machine (SVM) and Model-Averaged-Artificial-Neural-Network (Model-Averaged-ANN). In the present work, forecasting has been done for 12 months for the site which is located at of Gorakhpur, U.P., India. Ten methodological parameters have been taken to fit the models. All the methodological parameters data has been stored from Solar-Radiation-Resource-Setup (SRRS). From this analysis, it has been found that both SVM and Model Averaged ANN present good results up to 6 day-ahead forecasting. It is also found that the Model Averaged ANN presents better results than the SVM.

1. INTRODUCTION

Sun is the primary resource of every energy existing at this globe, it directly affects many agricultural, chemical, biological and solar power generation processes [1]. The GSR is the key element that shows the available solar power potential on the earth's surface [2], [3]. GSR forecasting may help to predict and identify how much solar energy will be available in the next few years or month or day or hour. Day-ahead GSR forecasting may help the utility to forecast electricity which may be generate by any solar-power-plant in the forthcoming time. The GSR has a non-linear characteristic because of its uncertainty or intermittency. For non-linear data Machine learning models present better results than time series models hence, Machine learning algorithms can model the GSR very well [4]. The SVM and ANN models are very prominent tools of machine learning algorithms[5], [6]. Some relevant researches in connection to this are briefly discussed hereunder:

Zeynab Ramedani *et al.* [7] have compared SVM and ANN models for GSR forecasting for a site location in Iran. Seven methodological variables had been used as the input variable and GSR had been used as an output variable in both the models. Radial function and polynomial function based SVM models and Levenberg–Marquardt training algorithm-based ANN model had been used in this case study for GSR forecasting. From the results, it has been found that the radial function based SVM model presented better results than the polynomial function based SVM model whereas, both these SVM models presented better results than Levenberg–Marquardt training algorithm based Neural Network. Ji-Long Chen [8] had compared twenty-one SVM-models containing dissimilar kernel-functions as well as input variables. In that case study, 28-year monthly data have been used for the analysis. Data had been collected from the data collection center in China. Various SVMs having different kernel functions and having different combinations of maximum temperature and minimum temperature as input-based models had been compared in the study. It had been found that polynomial kernel-based SVM having maximal and minimal temp. as the input variable presented the best results. Some literature based on the least square SVM was also reported [9][10]. Hanna Meyer [11] had compared four machine learning models for optical rainfall retrievals. In that case study Random Forest, ANN, SVM and Model Averaged ANN have been compared. It had been found that Model-Averaged-ANN shows better outcome than SVM and Random Forest Model.

From the Literature-survey, the observation is that SVM and ANN-models are presenting good results for GSR forecasting. Also, the radial function based SVM model shows better results than the polynomial based SVM model and ANN models [7]. It has also been found that the Model Averaged ANN model can present better results than other ANN models [10]. Hence, in this paper, the Model-Averaged-ANN model has been compared with radial kernel function based SVM. One-year hourly data has been

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used in this study for GSR forecasting for Madan-Mohan Malaviya-University of Technology (MMMUT), Gorakhpur, U.P., India. To examine result appropriately one to six-day-ahead GSR predictions have been achieved for every month of a year. Forecasting has been done on the R software platform [12].

The paper has been divided into 4 sections. Second section deals with methodologies used in the paper. In this section details of the site location, data set, SVM model, Model-Averaged-ANN model and various statistical parameters have been discussed. The third and most important part of the paper is dedicated for forecasting outcomes of SVM model and Model-Averaged-ANN model. In that segment, the findings of SVM-model, the findings of Model-Averaged-ANN along with a comparison of both these models have been discussed. In the fourth and the last section the analysis and comparison of the outcome have been discussed.

2. METHODOLOGY

2.1 Site Location and Data

The city Gorakhpur is situated in the north constituency of India. Gorakhpur is the nearest city just before the border of India and Nepal. The MMMUT is a technical University situated at Gorakhpur since 1962. The site location of MMMUT is at Latitude of26°43'50.41"North and Longitude of83°26'2.8"East. Google map view visualizing MMMUT is shown in Figure 1 [13].

Fig. 1. Site Location of the MMMUT.

Reliability of data is very important hence in this case study various metrological data have collected from SRRS which is mounted on the top of the Electrical-Engineering-Department, MMMUT, Gorakhpur [14][15]. Actual view of the SRRS is shown in Figure 2. In this case study, 1st January 2017 to 31st December 2017 (One Year) data has been used. Nine methodological data, Minimal Temp.(°C), Maximal Temp.(°C), Average Temp.(°C), Wind Speed(m/sec), Rain(mm), Dew Point(°C), GSR(w/m^2), Atmospheric Pressure(mb), and Solar Azimuth (°) have been collected for the setup.

Fig. 2. View of Data Collection Setup.

2.2 Model Averaged ANN

Artificial-Neural-Network (ANN) is a machine-learning model that has been developed as based on function of the human brain. It computationally simulates the behavior of neurons of the human brains for fitting the model [16]. There are various algorithms to model ANN structure such as feed-forward ANN, backpropagation ANN, Levenberg–Marquardt ANN, Deep learning ANN and Model Averaged ANN. Out of these Model Averaged ANN is a very promising neural network [11][17].

Model-Averaged-ANN is a special type of ANN which creates various ANN model and compiles there outcome to produce final outcome instance of generating a single ANN structure [18], [19]. This model firstly develops various ANN models having different weights, layers, input variables or other parameters and finally, the best-forecasted results of different models have been averaged to generate final forecasting outcome. The details of Model averaged ANN have been presented in the book authored by Ripley [20].

2.3 Support Vector Machine (SVM)

SVM is one of the supervised learning model which has been developed by Vapnik [21], [22]. The SVM models are widely used for regression and classification. The SVM model is based on the theory of structural-risk-minimization (SRM) principle which presents better results than traditional-empirical-risk-minimization (ERM) principle that is used in ANN modeling. The SRM minimizes the greater bound of generalization error that deals with both sums of training errors as well as a confidence levels based on the Vapnik–Chernoverkis dimension whereas ERM minimizes only training error [23]. The SVM model does the regression by the use of Kernel function which is high dimensional feature space. The SVM generates a unique solution because it works on the principle of the global optimal solution in the place of the local optimal solution as in ANN. Let us consider a set of data points are

$P = \{(x_a, d_a)\}_a^n$ (where, x_a is input vector, d_a is target value and n is the range of data . The SVM approximates the input-output relationship by the following formula [1], [7], [24], [25]:

$$f(x) = W\varphi(x) + B \tag{1}$$

where, $\varphi(x)$ is the dimension feature space mapped from the input x; Coefficient w and B can be estimated by minimizing the regularized risk function below:

$$R_{SVM}(c) = c\frac{1}{n}\sum_{a=1}^{n}(L_a, y_a) + \frac{1}{2}\|W\|^2 \tag{2}$$

where, $c\frac{1}{n}\sum_{a=1}^{n}(L_a, y_a)$ is the empirical error and it can be measured by function L_ε, L_ε can be calculated be fallows:

$$L_\varepsilon(d, y) = \begin{cases} |d - y| - \varepsilon\, |d - y| \geq \varsigma \\ 0 \quad otherwise \end{cases} \tag{3}$$

where, $\|W\|^2$ presents regularization, c is the error penalty parameter, ς is tube size. B and W can be calculated by transforming Eq. (2) into Eq. (3) by introducing new scale variables ε_a and ε_a^* as follows:

$$Minimize \quad R_{SVM}(W, \varepsilon^{(*)}) = \frac{1}{2}\|W\|^2 + c\sum_{a=1}^{n}(\varepsilon_a + \varepsilon_a^*) \tag{4}$$

$$Subjected \quad to \quad \begin{array}{l} d_a - W\varphi(x_a) - b_a \leq \varsigma + \varepsilon_a \\ W\varphi(x_a) + b_a - d_a \leq \varsigma + \varepsilon_a^*, \varepsilon_a^* \geq 0 \end{array} \tag{5}$$

Lastly, by addition Lagrange-multipliers as well as exploiting the optimality constraints, the decision fun. by Eq 1 has the final form:

$$f(x, y_a, y_a^*) = \sum_{a=1}^{n}(y_a - y_a^*)K(x, x_a) + b \tag{6}$$

From the eq. (6) terms $K(x_a, x_b)$ are known as the Kernel Function. The value of Kernel function is the vector product of x_a and x_b in the feature space of φ_a and φ_b, it means that $K(x_a, x_b) = \varphi(x_a) \times \varphi(x_b)$. There are three basic kernel-functions namely, Liner-Kernel-Function, Polynomial-Kernel-Function, and Radial-Kernel-Function. The Linear-Kernel-Function can be shown as $K(x_a, x_b) = x_a \times x_b$ Polynomial-Kernel-Function can be shown as $K(x_a, x_b) = (x_a \times x_b + 1)^d$ and Radial-Kernel-Function can be shown as $K(x_a, x_b) = \exp(-\gamma\|x_a \times x_b\|^2)$ wherever, d and γ are kernel parameters.

2.4 Performance Evaluation

For the SVM and Model Averaged ANN models have been evaluated based on Mean-Bias-Error (MBE), Root-Mean-Square-Error (RMSE) and Mean-Absolute-Error (MAE), as these are most significant statistical indicator [26]. MAE and RMSE shows the magnitude of the average error whereas MBE describe the direction of the error bias. These errors can be formulated as below:

$$MBE = \sum_{k=1}^{N} e / N \tag{7}$$

$$RMSE = \sqrt{\sum_{k=1}^{N} e / N} \tag{8}$$

$$MAE = \sum_{k=1}^{N} |e| / N \tag{9}$$

where, e is the error between the actual and forecasted values and N is the integer of interpretation.

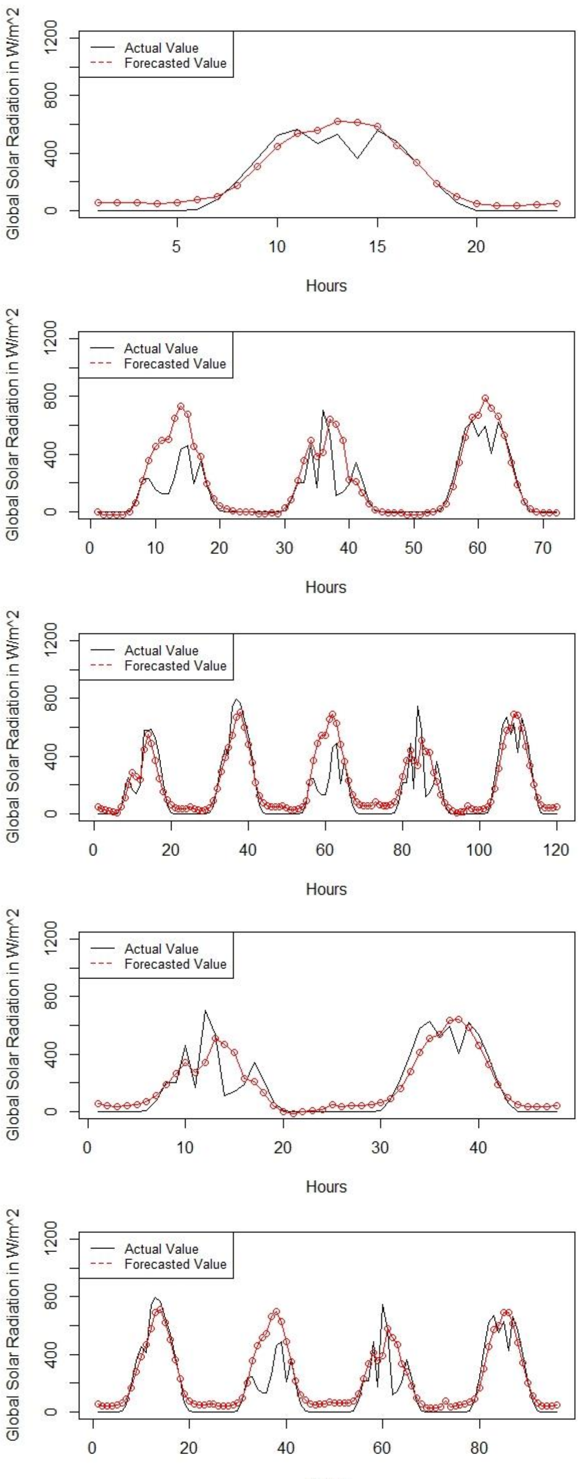
3. FORECASTING RESULTS

One to Six-day-ahead GSR prediction has been done on each and every month data for 2017 by the SVM model and Model Averaged ANN model. For both of the models, time and eight methodological variables have been taken as input variables whereas GSR has been taken as the target variable.

3.1 Performance of Modal Averaged ANN

For the Modal-Averaged-ANN forecasting, an ANN network having nine input layers ten hidden layers and one output layers containing 111 weights has been used. Five different neural networks with different random number seeds have been used for averaging of models. The R package "avNNet" has been employed for these forecasting [27]. Figure 3 shows one to six day-ahead forecasting and actual value graph in the month of May.

Table 1 represents various errors associated in Model-Averaged-ANN forecasting. From the results, it has been found that for one-day-ahead forecasting, the minimum forecasting errors are in the month of November whereas, the maximum forecasting errors are in the month of July and the average RMSE is 64.99%. For two-day-ahead forecasting, the minimum forecasting errors are found in the month of October whereas, the maximum forecasting errors are in the month of July and the average RMSE is 76.15%. In three-day-ahead forecasting, the minimum errors are in the month of October whereas, the maximum forecasting errors are in the month of May and the average RMSE is 70.20%. For four-day-ahead forecasting, the minimum forecasting errors are found in the month of October whereas, the maximum forecasting errors are in the month of May and the average RMSE is 64.39%. For five-day-ahead forecasting, the minimum forecasting errors are found in the month of October whereas, the maximum forecasting errors are in the month of May and the average RMSE is 68.81%. For six-day-ahead forecasting, the minimum forecasting errors are found in the month of October whereas, the maximum forecasting errors are in the month of May and the average RMSE is 75.48%



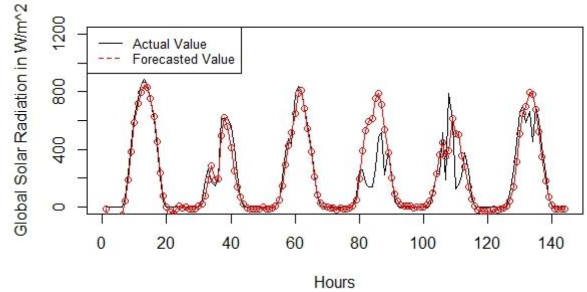
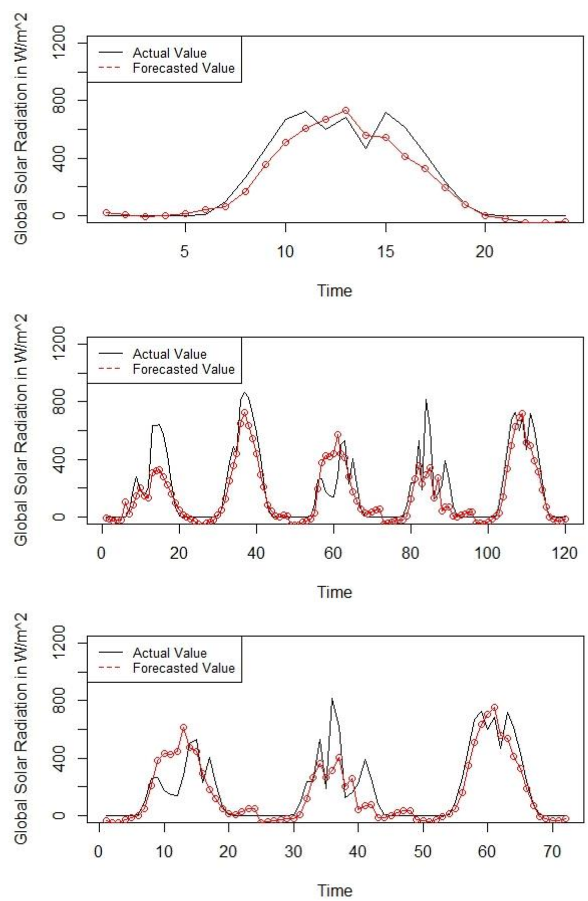
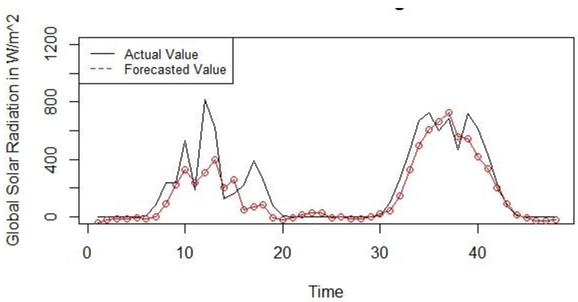


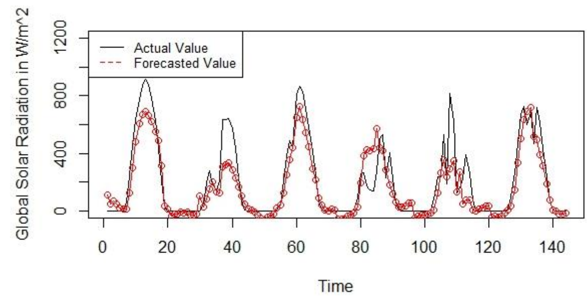
Fig. 3. Actual and Forecasted Value Graphs Associated from Model-Averaged-ANN Model Forecasting

3.2 Performance of SVM Model

Radial kernel function based SVM models have been used for GSR forecasting of all 12-month data on 2017 for site location of Gorakhpur, U.P., India. The R package "e1071" has been used for SVM model forecasting [28]. Figure 4 presents 1 to 6-day-ahead forecasting and actual results of the month of May.







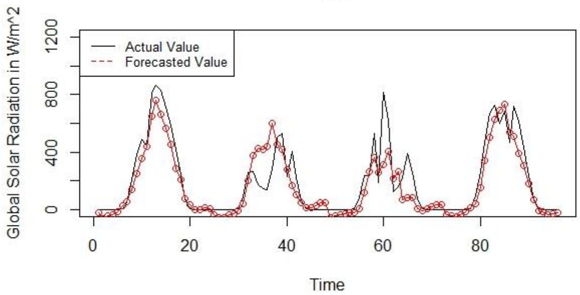


Fig. 4. Actual and Forecasted Value Graphs Associated from SVM Model Forecasting.

Table 1. Errors Associated in Model-Averaged-ANN Model Forcastings

Day-ahead Forecasting Spam	Errors	Jan17	Feb17	Mar17	Apr17	May17	Jun17	Jul17	Aug17	Sep17	Oct17	Nov17	Dec17
1	MBE	-45.07	-25.35	-26.58	-69.05	-35.08	-12.42	15.17	-5.61	-32.35	6.75	-0.62	-39.42
	RMSE	88.54	45.29	81.66	106.83	71.17	34.52	113.28	33.42	52.55	42.58	28.06	81.94
	MAE	55.33	32.89	67.50	69.05	52.80	27.11	72.94	21.46	42.90	35.28	20.85	51.69
2	MBE	-46.83	5.65	-0.99	-52.17	-10.85	13.27	37.72	-64.84	-41.16	-1.05	-8.31	-49.17
	RMSE	98.46	27.42	65.77	86.74	107.96	48.31	115.30	110.46	79.57	25.36	38.18	109.85
	MAE	59.60	23.16	34.26	53.44	70.75	37.52	66.33	75.47	49.91	20.27	24.42	71.67
3	MBE	-26.46	10.16	-3.96	-22.25	-49.70	18.06	10.97	-59.45	-19.22	8.36	-10.02	-22.75
	RMSE	75.31	25.98	57.89	77.38	144.86	50.54	92.50	130.74	57.62	24.90	37.59	67.06
	MAE	47.69	20.78	30.82	34.52	80.72	34.96	55.16	75.71	44.75	20.21	24.08	42.94
4	MBE	10.77	17.91	-26.56	-18.84	-46.67	25.8	3.02	-42.23	-21.99	8.13	-10.20	21.64
	RMSE	55.49	33.60	58.77	66.12	127.02	61.89	89.68	92.47	55.59	23.91	36.47	71.67
	MAE	38.10	24.80	47.69	26.85	86.49	45.24	53.58	58.07	43.76	19.70	24.35	46.76
5	MBE	1.07	42.11	-21.91	-5.64	-31.14	27.95	-1.63	-41.14	-19.79	13.86	-6.38	0.63
	RMSE	81.29	54.71	59.16	61.94	118.68	67.16	85.99	87.35	55.12	32.08	47.84	74.45
	MAE	50.68	43.44	33.93	30.28	80.01	49.18	49.37	57.63	45.27	26.02	30.94	45.87
6	MBE	6.72	57.95	-20.54	20.14	-3.74	25.70	-8.36	-34.37	-25.69	21.28	-11.28	5.00
	RMSE	74.09	77.02	62.98	76.46	120.57	71.86	91.52	73.43	78.61	35.93	73.13	70.21
	MAE	42.48	61.28	34.43	42.75	67.01	53.47	54.20	48.69	52.11	30.82	39.66	44.37

Table 2. Errors Associated in SVM Model Forcastings

Day-ahead Forecasting Spam	Errors	Jan17	Feb17	Mar17	Apr17	May17	Jun17	Jul17	Aug17	Sep17	Oct17	Nov17	Dec17
1	MBE	-3.75	-22.04	25.11	-27.00	40.10	-37.48	11.62	61.22	22.20	17.32	6.87	-3.27
	RMSE	18.54	44.73	94.99	135.51	85.30	78.59	130.71	114.13	70.67	45.72	67.87	16.35
	MAE	14.55	37.20	68.82	79.96	63.21	59.32	87.34	66.82	41.84	38.57	44.15	12.61
2	MBE	-22.81	-17.84	44.49	-6.05	59.01	-12.72	31.41	-13.33	5.41	3.37	0.32	-20.50
	RMSE	51.48	48.70	99.36	103.46	125.89	79.87	128.44	103.42	59.40	34.13	53.64	46.31
	MAE	34.08	41.21	74.16	60.64	81.06	61.01	78.54	64.31	38.64	29.14	35.05	30.65
3	MBE	-21.90	10.44	32.86	-18.04	28.08	15.05	32.86	-44.99	20.74	12.93	15.53	-19.70
	RMSE	62.71	51.67	97.44	91.64	128.56	116.10	117.17	111.86	81.18	36.57	74.11	56.44
	MAE	45.04	43.55	68.41	56.63	87.18	77.43	67.04	71.26	53.28	30.83	47.59	40.54
4	MBE	11.33	18.32	6.74	-12.78	38.47	12.54	-7.89	-32.58	25.84	10.29	16.27	4.96
	RMSE	62.42	58.21	59.95	87.63	119.33	113.43	106.08	100.25	92.18	37.14	73.66	75.64
	MAE	36.45	44.80	42.39	55.24	82.65	80.17	68.56	65.24	63.23	31.88	47.56	48.88
5	MBE	-20.60	24.32	4.41	-20.88	49.75	21.08	-13.86	-26.59	16.65	17.11	8.28	-18.52
	RMSE	111.72	65.37	58.17	90.21	127.71	122.19	100.14	96.02	85.40	45.71	75.39	100.54
	MAE	74.27	49.40	41.24	63.15	86.33	91.08	66.53	64.31	57.87	37.60	49.91	66.85
6	MBE	-16.03	19.05	-25.41	4.67	47.74	38.96	-7.00	-27.21	6.73	23.62	-0.02	-14.43
	RMSE	103.53	73.89	85.44	101.71	124.01	147.87	100.06	91.35	91.31	48.66	77.72	93.17
	MAE	67.26	54.19	66.03	73.60	85.57	112.27	67.50	63.17	59.78	40.55	50.27	60.53

3.3 Comparison

The RMSE is the most important statistical parameter to check the forecasting performance of any model hence, Model-Averaged-ANN and SVM model have been compared based on RMSE. Figure 5 presents a comparison of Model-Averaged-ANN and SVM model for one to six-day-ahead forecastings for every month based on RMSE. Figure 5(a) presents the RMSE graph for one-day-ahead forecasting in every month. From this figure, we may observe that RMSE of Model-Averaged-ANN is less than the SVM model except in the month of January and December and Avg. RMSE of Model-Averaged-ANN model is also quite less than the SVM model for 1-day-ahead forecasting. Figure 5(b) presents the RMSE graph for two-day-ahead forecasting in various months. From this figure, we may observe that RMSE of Model-Averaged-ANN is below the SVM model within most of the cases and the avg. RMSE of Model-Averaged-ANN model is also less than SVM model for 2-day-ahead forecasting. Figure 5(c) presents the RMSE graph for three-day-ahead forecasting within every month. From figure 5(c) it may be observed that RMSE of Model-Averaged-ANN is below the SVM-model in most of the cases and the avg. RMSE of Model Averaged ANN model is also less than SVM model for three-day-ahead forecasting. Figure 5(d) presents the RMSE graph for 4-day-ahead forecasting in every month. From this figure, we may observe that RMSE of Model Averaged ANN is less than the SVM model except in the month of May and the Avg. RMSE of Model-Averaged-ANN model is also less than the SVM model for four-day-ahead forecastings. Figure 5(e) presents the RMSE graph for four-day-ahead forecasting in every month. From figure 5(e) it may be observed that RMSE of Model-Averaged-ANN is less than the SVM model except in the month of March and the avg. RMSE of Model-Averaged-ANN model is also less than SVM model for five-day-ahead forecasting. Figure 5(f) presents the RMSE graph for six-day-ahead forecasting in every month. From this figure, we may observe that RMSE of Model-Averaged-ANN is less than the SVM model except in the month of February and the avg. RMSE of Model-Averaged-ANN model is also less than the SVM model for six-day-ahead forecasting. Hence from the observations, it can say that Model-Averaged-ANN is presenting quite better results than SVM in this case study.

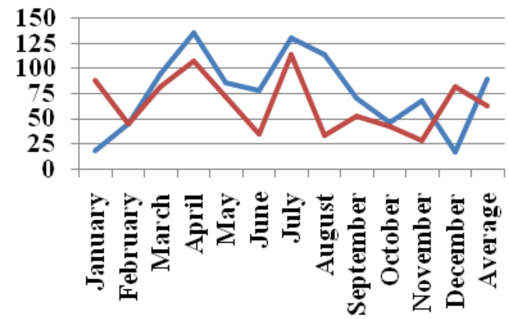
A thorough study of the findings reveals that both the Model-Averaged-ANN and SVM models exhibit strong performance. Viewing the differences between the results of the one-day forecasting and the six-day forecasting, we notice that in the case of Model-averaged-ANN, the differences between the RMSEs of the one-day forecasting and the RMSEs of the six-day forecasting were just 10.49%, whereas in the case of SVM model, the differences were 19.64%, both of which were within acceptable bounds. This demonstrates that we would achieve acceptable results if we extended the forecasting day-ahead period. Additionally, a longer day-ahead forecasting period is preferable to a shorter one. We can accurately predict the value of solar radiation if we want to predict its availability up to 6 days in advance (within standard prescribed limits). Numerous applications, including predictions of solar power availability, analysis of the thermal loads on buildings, studies of the energy balance of the atmosphere, aspects of farming, and sun-dependent industries, can benefit from these findings.

4. VALIDATION OF FORECASTING RESULTS

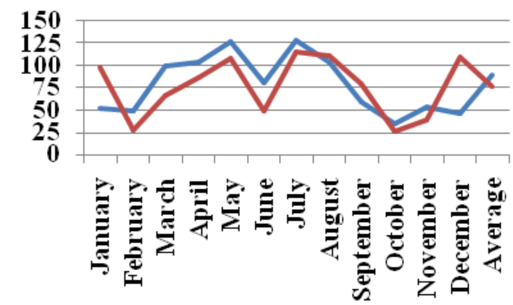
Even though MBE, RMSE and MAE are good performance indicators but they are not able to validate the forecasting results. The t-static error can validate the results to check whether the results are statistically significant or not. Standard t-static error provides standard values of the t-static error below which value of t-static error, forecasting results are statistical significate [29]. The t-static errors could be computed as:

$$t = \left[\frac{(N-1)(MAE)^2}{(RMSE)^2 - (MAE)^2} \right]^{1/2} \tag{10}$$

Table 3 presents calculated and standard-t-static errors at 95% confidence-level. Table 3 (a) shows the t-static error of Model-Averaged-ANN model and Table 3 (b) shows the t-static error of SVM model. From the tables, it may be notice that in all cases t-static error is less than the stander-t-static error hence all the forecasting results are statistically significant.



(a)



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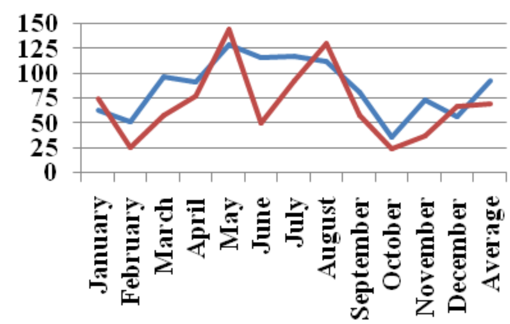

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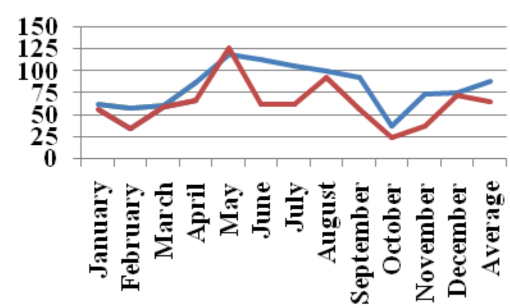
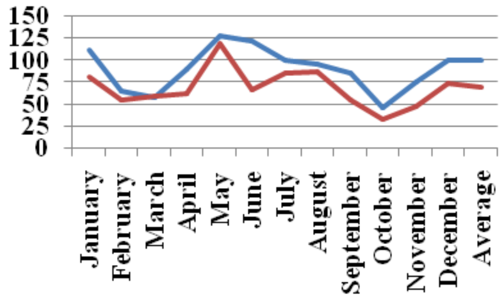


(d)



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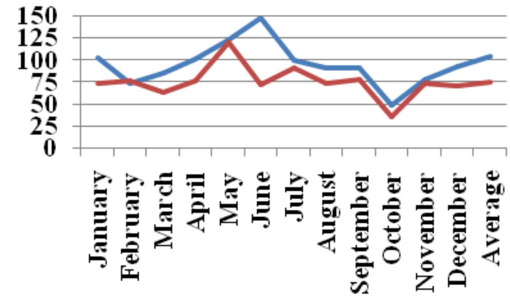

(f)

SVM Model Averaged ANN

Fig. 5. Comparison of (a) one-day-ahead (b) two-day-ahead (c) three-day-ahead (d) four-day-ahead (e) five-day-ahead (f) six-day-ahead Forecasting RMSE in all months of 2017.

Table 3. The t-static error from Model Averaged ANN and SVM model and Standard-t-static error

Day-ahead Forecasting Spam	**Jan17**	**Feb17**	**Mar17**	**Apr17**	**May17**	**Jun17**	**Jul17**	**Aug17**	**Sep17**	**Oct17**	**Nov17**	**Dec17**	**Standard-t-static error values at 95% confidence-level** [29]
(a) Model-Averaged-ANN Model													
1	0.39312	-0.080474	0.050224	0.41348	-0.29308	-0.1267	-0.14361	-0.70822	-0.3499	-0.49426	-0.41806	0.40209	2.069
2	0.52722	-0.32659	-0.44072	0.3172	-0.36524	-0.20822	-0.78442	0.24452	-0.0049859	-0.22899	-0.36967	0.80675	2.013
3	0.34691	-0.50489	-0.46829	0.11178	0.60619	-0.35131	-0.21861	0.4098	-0.56628	-0.44649	-0.40684	0.29701	1.994
4	-0.43651	-0.78825	0.09857	0.043148	0.88356	-0.57877	0.031304	0.034966	-0.5522	-0.51321	-0.46086	-0.67082	1.984
5	0.27597	-1.1556	-0.039957	-0.13617	0.51468	-0.71042	0.19653	0.007889	-0.64021	-0.72154	-0.63353	0.29328	1.98
6	0.054505	-1.3133	-0.089827	-0.94975	-0.076747	-0.73155	0.462	-0.14762	-0.44295	-1.0153	-0.45173	0.10738	1.976
(b) SVM Model													
1	0.1816	0.27833	-0.34386	0.33469	-0.49965	0.42531	-0.16586	-0.84748	-0.29568	-0.20792	-0.12497	0.18182	2.069
2	1.1341	0.30241	-0.85798	0.099951	-1.211	0.19939	-0.74459	0.25003	-0.10232	-0.05398	-0.0083254	1.1329	2.013
3	0.96143	-0.22433	-0.82997	0.34788	-0.7429	-0.30017	-1.0705	0.96709	-0.49177	-0.25952	-0.50027	0.96109	1.994
4	-0.48598	-0.46787	-0.18809	0.27782	-1.1037	-0.28626	0.2648	0.82275	-0.7163	-0.24082	-0.60838	-0.23608	1.984
5	0.97231	0.68579	-0.13689	0.49717	-1.679	-0.56005	0.485	0.76422	-0.5323	-0.44752	-0.35973	0.97127	1.98
6	0.77987	-0.58943	0.87091	-0.12347	-1.6391	-1.1973	0.27867	0.88859	-0.2318	-0.68285	0.0012614	0.78021	1.976

5. CONCLUSIONS

In this case study, GSR one to six-day-ahead hour-wise prediction has been achieved using SVM and Model-Averaged-ANN for the whole month of 2017 for the city Gorakhpur. A total of 10 input variables are selected for these forecasting. Authentic records have been chosen for the study that have been secured from the SRRS. The various outcomes come from this study have been given below:

- This paper presents GSR forecasting on an hourly basis which will be helpful in the estimation of available solar-power each hour. This type of prediction outcomes certainly advantageous for independent-System-Operators (ISO) in there bidding process.
- Both SVM and Model Averaged ANN models are presenting very good results and also, these models present good results up to for 6-day-ahead forecasting hence these models can be employed up to for 6 day-ahead forecastings.
- Forecasting errors are high in raining months because the variation in the GSR is high in these seasons due to clouds in India whereas in winter forecasting errors are less because in winter seasons lesser variation in GSR is found.
- For this case study, the Model Averaged ANN model presents better results than the SVM model.

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